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CLOSED-LOOP BRAIN–COMPUTER INTERFACES (BCI) ENHANCED WITH AI-DRIVEN NEUROFEEDBACK USING SOFT BIOELECTRONIC NETWORKS: A COMPARATIVE STUDY WITH I-BRAINTECH AND PROPOSAL OF A NEW HYBRID MODEL

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ABSTRACT

This paper explores recent advancements in soft, flexible bioelectronic neural networks for multi-site brain monitoring and evaluates their potential when compared to commercially available brain–computer interface (BCI) technologies, particularly those developed by i-BrainTech. Soft bioelectronic technologies, which are constructed from stretchable, ultrathin, and biocompatible materials, represent a major leap forward in neural interfacing due to their ability to conform to complex brain geometries, minimize tissue irritation, and enable highdensity, minimally invasive data acquisition from multiple cortical and subcortical regions. These properties allow continuous, stable recording of electrophysiological signals, including local field potentials (LFPs) and intracranial EEG (iEEG), with improved spatial resolution and long-term biostability. Consequently, they offer a new paradigm for capturing detailed neural dynamics during motor, cognitive, and sensory processing—capabilities that existing EEG-based commercial BCIs often struggle to achieve due to their susceptibility to noise, limited signal depth, and lower spatial localization accuracy. In contrast, i-BrainTech, a leading company in commercial BCI neurotechnology, focuses primarily on noninvasive EEGbased neurotraining platforms designed for motor and cognitive rehabilitation. Their system utilizes surface electrodes to record brain signals during motor imagery tasks, which are then processed through AI-based algorithms to provide realtime neurofeedback and assist patients in improving motor function, attention, and neurocognitive performance. Although i-BrainTech's approach is clinically accessible, cost-effective, and patient-friendly, particularly for stroke survivors and athletes requiring rehabilitation, it remains limited by the inherent constraints of surface EEG—including low signal fidelity, poor spatial resolution, and high susceptibility to artifacts from muscle movement and environmental interference. These limitations make it challenging to precisely target specific neural regions involved in rehabilitation, potentially reducing the overall effectiveness of neurotraining. By critically analyzing both approaches—advanced soft bioelectronics and i-BrainTech's EEG-based neurotraining platform—we propose a novel hybrid closed loop BCI architecture that integrates the strengths of each technology. The proposed system combines soft implantable bioelectronic sensors for precise intracranial signal acquisition, wearable EEG systems for broad noninvasive monitoring, and machine learning–based adaptive neurofeedback mechanisms. This architecture improves neural signal fidelity, expands the range of measurable brain regions, and enables multi-modal data fusion for enhanced motor and cognitive rehabilitation outcomes. By incorporating both invasive and noninvasive modalities, the system balances precision with practicality, allowing for customizable deployment tailored to user needs and clinical severity. The hybrid model operates on a closed-loop framework, in which neural signals gathered from both intracranial and surface-level sensors are continuously analyzed using advanced AI-driven signal processing and classification models. These models identify patterns related to motor intention, cognitive engagement, or neuroplasticity markers and automatically adjust neurostimulation or feedback parameters. Through adaptive learning algorithms, including reinforcement

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learning and patient-specific modeling, the system progressively personalizes therapeutic interventions, ensuring that neurofeedback remains optimized for each individual's rehabilitation progress over time. This leads not only to improved signal accuracy and therapeutic efficacy but also contributes to long-term enhancements in neural recovery, plasticity, and functional independence. Furthermore, the integration of soft bioelectronics with noninvasive EEG technologies addresses several limitations associated with traditional BCI platforms. For example, intracranial soft electrodes provide high-fidelity signals from deep or localized brain regions, while EEG sensors capture broader cortical activity—together forming a comprehensive overview of the brain's electrofunctional behavior. This multi-layered data fusion allows for enhanced monitoring of neural recovery mechanisms, making it particularly useful in clinical scenarios such as post-stroke rehabilitation, Parkinson's management, sports neurotraining, and cognitive enhancement therapies. In summary, this paper demonstrates that combining soft bioelectronic implants with conventional EEG-based systems and AI-driven closed-loop neurofeedback results in a next-generation hybrid rehabilitation platform. This approach leverages the precision of invasive sensing, the convenience of wearable technologies, and the adaptability of intelligent machine learning algorithms. The proposed hybrid BCI model offers a promising pathway to overcoming the limitations of current commercial systems, delivering improved neural monitoring accuracy, enhanced motor and cognitive recovery outcomes, and a more scalable and personalized solution for future rehabilitation technologies.

KEYWORDS

Soft Bioelectronics; Brain–Computer Interface (BCI); Closed-Loop System; Neurofeedback; AI-Based Neural Decoding; Motor Rehabilitation; i-BrainTech

1. INTRODUCTION

Interpretation of neural signals, which fundamentally limits the user's ability to adapt during training and constrains the overall effectiveness of rehabilitation. In such systems, neural activity is passively decoded without generating responsive feedback that adapts to the user's ongoing performance or neural state. This lack of dynamic interaction reduces the system's capacity to support long-term neuroplasticity, making it difficult to optimize recovery processes in motor rehabilitation or cognitive enhancement. Recent advances in neural engineering, however, are beginning to address these limitations. In particular, progress in soft bioelectronic networks has introduced highly flexible, minimally invasive neural interfaces capable of capturing high-resolution electrophysiological data across multiple cortical and subcortical sites. Because these devices conform to the three-dimensional curvature of brain tissue and maintain stable long-term contact, they significantly reduce inflammation, tissue damage, and signal drift, thereby enabling more reliable monitoring of neural activity during rehabilitation exercises or neurofeedback tasks. At the same time, the commercial neurotechnology sector has evolved rapidly, with companies like i-BrainTech emerging as prominent leaders in noninvasive BCI-based neurotraining. i-BrainTech has developed an EEG-driven motor imagery training platform designed to help users enhance motor skills, recover post-stroke motor function, and strengthen cognitivemotor coordination through repeated neurotraining tasks. Their system, often used by elite athletes and rehabilitation patients, provides an accessible and user-friendly interface that enables users to practice neural control through real-time feedback in a game-like virtual environment. Despite its accessibility and commercial success, noninvasive EEG-based systems continue to face inherent limitations. These include low spatial resolution due to the distance between scalp electrodes and neural sources, susceptibility to movement artifacts and electrical noise, and the inability to selectively monitor activity from specific cortical layers or deep brain regions. Furthermore, many commercial systems still rely on partially open-loop paradigms or fixed feedback parameters, resulting in limited personalization and slower adaptation for users with diverse neurological profiles. Given these contrasting yet complementary technological directions, there is growing interest in integrating the strengths of high-resolution soft bioelectronic networks with the scalability and comfort of EEG-based neurotraining tools such as those offered by i-

BrainTech. This paper begins by comparing the capabilities, limitations, and application contexts of two major categories: (1) soft bioelectronic networks engineered for multi-site intracranial monitoring and (2) i-BrainTech's Neuro Zone motor training platform, which represents the current state of commercially deployed noninvasive neurotraining. Through this comparative analysis, we highlight how soft, implantable bioelectronics provide unparalleled spatial precision and stability, while commercial EEG-based BCIs excel in usability, accessibility, and real-world deployment. Building on this dual analysis, the paper proposes a novel AI-driven closed-loop hybrid BCI architecture that synergistically merges the core principles of both technologies. The envisioned system utilizes soft bioelectronic implants to gather detailed neural signals from targeted brain regions related to motor intention, sensorimotor integration, or cognitive control. These high-fidelity signals are then combined with broader cortical activity captured by wearable EEG sensors, creating a multi-layer, multi-resolution neural data stream. Machine learning models—integrating deep neural networks, reinforcement learning, and adaptive decoding algorithms—continuously analyze the incoming signals to detect meaningful neural patterns and guide real-time adjustments to feedback, stimulation intensity, or training difficulty. By unifying implant-grade precision with wearable-grade accessibility, the proposed hybrid BCI aims to overcome longstanding limitations in rehabilitation technologies. The system offers the potential for deeply personalized neurotraining, optimized neuroplasticity induction, and superior rehabilitation outcomes for users ranging from stroke survivors and individuals with motor impairments to professional athletes seeking high-performance neurotraining. Ultimately, this hybrid closed-loop model illustrates a pathway toward next-generation BCI platforms capable of delivering both the accuracy required for medical-grade interventions and the usability necessary for widespread adoption.

2. Methods

2.1. Soft Bioelectronic Networks for Multi-Site Sensing

The proposed soft bioelectronic system is engineered using ultra-flexible, biocompatible materials specifically designed to match the mechanical properties of neural tissue. Unlike conventional rigid electrodes, which often introduce mechanical stress and provoke immune responses, these soft materials bend, stretch, and deform in accordance with natural brain movements, thereby maintaining stable interfacing conditions. This material compatibility greatly reduces the risk of tissue irritation and supports long-term implantation without compromising neural integrity. Embedded within this flexible substrate is a high-density array of microelectrodes that dramatically increases the spatial resolution of neural recordings. The tight spacing between electrodes allows the system to capture subtle variations in cortical surface potentials that would otherwise be obscured in lower-density configurations, providing a richer and more detailed representation of local and distributed neural activity. To complement its structural flexibility, the system incorporates an advanced wireless multi-channel communication framework. This architecture eliminates the physical constraints associated with traditional wired neural interfaces, which limit patient mobility, introduce noise through cable movement, and carry risks of infection at connector sites. By employing low-power wireless telemetry, the system can transmit large volumes of electrophysiological data across multiple channels in real time, enabling continuous longterm monitoring without disturbing the natural behavior of the patient or research subject. Such wireless capability is critical not only for chronic clinical applications but also for experimental studies requiring minimally intrusive recording environments. Furthermore, the ability of the device to form a conformal, intimate contact with the cortical surface ensures consistent electrical coupling, reducing impedance variability and enhancing the quality of signal acquisition over extended periods. The long-term stability of this bioelectronic platform is further supported by its biocompatible encapsulation and optimized electrode materials, which are engineered to minimize foreign-body responses. Over time, many implanted neural interfaces suffer from glial scarring, inflammation, and encapsulation that degrade signal fidelity. The soft, tissue-mimicking construction of this system helps mitigate such responses, preserving electrode performance and enabling reliable operation for months or even years—an essential requirement for chronic neurorehabilitation, brain–machine interfacing, and longitudinal neuroscience research. This durability expands the potential applications of the system far beyond acute laboratory experiments, positioning it as a robust tool for long-term neural monitoring and adaptive closed-loop BCI interventions. Functionally, the platform is capable of recording neural surface potentials from multiple cortical regions simultaneously, offering unprecedented insight into distributed brain network activity. This multi-site capability is especially important for analyzing interactions across motor, sensory, and cognitive regions, which rarely operate in isolation during real-world tasks. By collecting data from various cortical sites at high resolution, the system enables researchers to reconstruct multiregion communication patterns, identify functional connectivity changes, and observe the dynamic coordination of neural circuits underlying behavior, learning, and rehabilitation. The high-fidelity signal acquisition allows the system to detect fine temporal features, oscillatory rhythms, and localized cortical activations that are often lost in conventional EEG recordings due to volume conduction and signal mixing. In addition to static recording, the system supports real-time neural activity mapping, providing immediate visualization and analysis of brain dynamics. This capability is essential for closed-loop BCI applications, where neural signals must be rapidly processed and fed back to the user through visual, auditory, or neuromodulatory stimuli. The ability to map activity in real time enables responsive adaptation of training protocols, therapeutic interventions, and stimulation parameters based on the user's current neural state. For example, during motor rehabilitation, the system can identify early neural signatures of movement intention and use them to trigger feedback that reinforces appropriate motor pathways. Similarly, during cognitive tasks, real-time mapping can help detect attentional fluctuations and modulate task difficulty accordingly. Moreover, the multi-region interaction analysis supported by this platform opens the door to studying complex neural phenomena such as cross-regional synchronization, motor–sensory integration, and cognitive–motor coupling. These analyses provide valuable insight into how different parts of the brain coordinate to support voluntary movement, perception, memory, and higher cognition. In practical applications, such as neurorehabilitation, understanding these interactions enables the design of personalized interventions that target specific neural circuits involved in recovery. In research contexts, this capability allows scientists to explore how neural networks reorganize following injury or training, providing a deeper understanding of neuroplasticity mechanisms. Overall, the combination of ultra-flexible materials, highdensity microelectrode arrays, wireless multi-channel architecture, and long-term biostability results in a soft bioelectronic system that offers unprecedented performance for neural monitoring. Its functional capabilities—including precise multi-site recording, high-fidelity signal collection, real-time mapping, and sophisticated cross-regional analysis—make it a highly versatile tool for next-generation brain–computer interface technologies, clinical rehabilitation frameworks, and fundamental neuroscience research.

2.2. i-BrainTech Neuro Zone Platform

i-BrainTech's neurotechnology platform is built around a noninvasive EEG-based system designed to decode motor intention and support both cognitive and motor performance enhancement. By relying on scalp-level electrical recordings, the system captures neural patterns associated with imagined or attempted movements and translates them into usable control signals. These signals are then integrated into a series of structured neurotraining tasks, allowing users to engage in motor imagery exercises that are specifically engineered to promote neuroplasticity. Through repeated engagement with these tasks, individuals undergoing rehabilitation—such as stroke survivors or athletes recovering from injury—can strengthen neural pathways associated with motor planning and execution. Central to the platform's functionality is the application of AI-driven pattern classification algorithms. These algorithms analyze noisy surface-level EEG data and identify recurring neural signatures linked to desired motor intentions or cognitive states. The system continuously refines its classification accuracy by learning from user performance, enabling progressively more precise detection of motor-related brain activity. Once decoded, these neural signals are used to drive real-time feedback loops within interactive virtual environments. For example, users may control virtual objects, navigate training scenarios, or receive performance scores based on their neural activity patterns. Such real-time feedback enhances engage- ment, reinforces correct neural activation, and helps users develop stronger cognitive-motor associations. In addition to its signal processing capabilities, i-BrainTech provides an ecosystem of sports- and rehabilitation-oriented software modules. These modules are designed to address the needs of diverse user populations, ranging from professional athletes seeking performance optimization to patients requiring structured motor recovery. The neurotraining programs integrate principles from neuroscience, motor learning, and sports psychology, offering tailored training flows that encourage the development of motor coordination, focus, reaction time, and cognitive stamina. The system's emphasis on usability, comfort, and accessibility allows it to be deployed in clinical settings, sports facilities, and home environments, contributing to its broad adoption in the noninvasive BCI market. Despite these strengths, noninvasive EEG-based systems like i-BrainTech face several inherent limitations rooted in the physics and physiology of surface-level neural recording. One major limitation is the low spatial resolution of EEG signals, which results from the electrical conduction through the skull, cerebrospinal fluid, and scalp tissues. This blurring effect makes it difficult to isolate activity from specific cortical regions or capture fine-grained neural dynamics. As a consequence, the system cannot achieve the same level of precision as invasive bioelectronic interfaces that directly contact the cortical surface. Furthermore, the limited coverage of scalp electrodes restricts the system's ability to monitor widespread, multi-site cortical interactions, which are essential for understanding complex motor and cognitive processes. Another significant constraint is the absence of long-term adaptive closed-loop stimulation within the i-BrainTech platform. Although the system provides real-time visual and interactive feedback, it does not deliver neural stimulation or adaptive neuromodulation capable of directly shaping neural circuits. This reduces its ability to induce targeted neuroplastic changes compared to closed-loop invasive interfaces that can combine neural monitoring with electrical or optogenetic stimulation. Over time, the lack of adaptive modulation may limit rehabilitation progress, particularly for users with severe neural impairments who benefit from more direct circuit-level engagement. Additionally, because the platform relies entirely on surface EEG signals, it is sensitive to variations in user attention, mental fatigue, and environmental noise. EEG signals are easily disrupted by muscle movements, blinking, jaw tension, and electrical interference from surrounding devices. These factors can degrade decoding accuracy and introduce variability in performance across sessions. As a result, the effectiveness of the system depends heavily on the user's ability to maintain consistent attention and mental engagement during neurotraining tasks, which can be challenging for individuals with cognitive deficits, fatigue, or neurological disorders. Taken together, i-BrainTech's suite of technologies provides an accessible and user-friendly noninvasive BCI solution with strong applicability in cognitive-motor training and rehabilitation. However, its limitations—low spatial resolution, limited cortical coverage, lack of long-term adaptive stimulation, and reliance on surface-level signals—highlight the need for hybrid approaches that integrate the strengths of both noninvasive and invasive systems. These constraints also motivate the development of next-generation BCI architectures that combine soft bioelectronic implants with EEG-based sensing and AIdriven closed-loop feedback, offering a path toward enhanced precision, personalization, and therapeutic effectiveness.

2.3. Proposed Hybrid Sensing Architecture

We propose a dual-layer neural sensing architecture that integrates the strengths of both invasive and noninvasive modalities in order to achieve high-resolution, system-level brain monitoring suitable for advanced closed-loop BCI applications. The first component of this hybrid framework is an invasive layer built upon a soft bioelectronic network that interfaces directly with the cortical surface. This layer provides multi-site cortical monitoring across targeted neural regions such as the primary motor cortex (M1) and the supplementary motor area (SMA), which play essential roles in motor planning, execution, and motor–cognitive integration. By using ultraflexible, biocompatible materials, the invasive layer delivers high-bandwidth neural recordings with significantly reduced noise and distortion, enabling the capture of electrophysiological signatures that are otherwise inaccessible to noninvasive systems. The direct contact with neural tissue minimizes impedance variability and supports stable long-term operation, allowing the system to detect subtle oscillatory patterns, localized activations, and inter-regional communication with exceptional precision. Complementing this invasive component is a noninvasive layer consisting of a wearable EEG headset designed to provide whole-brain state monitoring in a comfortable, userfriendly form. While the invasive layer focuses on highresolution data from specific cortical sites, the EEG headset offers a broader view of overall brain dynamics, capturing global patterns associated with cognitive engagement, mental fatigue, arousal levels, and attentional fluctuations. These large-scale neural rhythms are essential for understanding how users interact with the system, how engaged they remain during neurotraining tasks, and how fluctuations in cognitive load may influence motor intention decoding. Because the EEG headset can be worn without surgical intervention, it also serves as a practical everyday interface that maintains continuity of monitoring outside clinical or laboratory environments. To unify the data streams produced by these two sensing layers, the system employs an integrated sensor fusion pipeline that combines statistical and deep learning-based temporal decoding methods. At the core of this fusion strategy is a Kalman filtering framework that aligns and smooths signals from the invasive and noninvasive channels, compensating for differences in sampling rates, noise characteristics, and spatial specificity. The Kalman filter acts as an optimal estimator, producing a coherent representation of underlying neural states by weighting each data source based on its uncertainty and reliability. This filtering provides a stable foundation for the subsequent application of long short-term memory (LSTM) networks, which excel at modeling the temporal dynamics inherent to neural activity. The LSTM-based temporal decoder analyzes fused neural signals to extract time-dependent patterns associated with motor intention, cognitive shifts, and cross-regional interactions. By leveraging the complementary strengths of both layers—fine-grained cortical data from the invasive interface and broad, state-dependent EEG information from the wearable headset—the LSTM decoder constructs a richer and more accurate representation of the user's neural trajectory. This enables more reliable prediction of motor intentions, more adaptive feedback modulation, and improved robustness in real-world environments where either invasive or noninvasive signals alone would be insufficient. Overall, this dual-layer sensing architecture provides a synergistic approach to next-generation brain–machine interfacing. The invasive layer delivers precision and high signal fidelity from targeted cortical structures, while the noninvasive layer captures global cognitive and attentional states. Their integration through advanced sensor fusion techniques establishes a comprehensive, multi-resolution neural monitoring platform capable of supporting personalized, adaptive, and high-performance closed-loop BCI systems.

2.4. AI-Based Closed-Loop Neurofeedback

The system integrates advanced neural interface technology with adaptive computational algorithms to deliver optimal stimulation and feedback patterns tailored to each individual user. At its core, the platform leverages Reinforcement Learning (RL) to continuously evaluate how different sensory or cognitive stimuli influence the user's neural responses. Instead of relying on predefined rules, the RL engine autonomously discovers which type of stimulation—whether visual, tactile, auditory, or multimodal—produces the highest learning efficacy for that specific user. Importantly, the RL component is designed to account for individual neural response dynamics, such as variations in synaptic responsiveness, attention span, fatigue accumulation, and the user's moment-to-moment cognitive state. As a result, the system can dynamically adjust the challenge level, increasing or decreasing task difficulty in real time to maintain an optimal zone for engagement and neuroplasticity-driven learning. Complementing the RL module, the platform incorporates Deep Learning–based neural decoders capable of analyzing high-dimensional, multi-site brain signals with exceptional precision. These decoders use a hybrid architecture that combines Convolutional Neural Networks (CNNs) with Recurrent Neural Networks (RNNs). The CNN layers extract spatial patterns across electrode arrays—identifying distributed activation maps or localized neural signatures—while the RNN layers model the temporal dynamics that unfold over milliseconds to seconds, such as the buildup of motor intention or the rise and fall of cognitive workload. This hybrid decoding approach allows the system to infer complex neural states, including motor imagery, volitional movement intention, and internal cognitive load, with far greater accuracy than traditional signal-processing methods. Beyond decoding momentary brain states, the system incorporates a predictive neuroplasticity modeling framework. This long-term modeling capability estimates how the user's neural circuitry is likely to adapt over repeated training sessions. It predicts which neural pathways will strengthen, what type of stimulation schedule will maximize learning, and how the user's functional abilities may evolve over weeks or months. Using these predictions, the system automatically constructs a personalized rehabilitation or training pathway, ensuring that each user receives a customized sequence of tasks and stimuli that optimally supports their motor recovery, cognitive enhancement, or behavioral training goals. For example, a motor-rehabilitation patient may receive stimulation patterns specifically tuned to reinforce weakened neural connections, while a student with ADHD may be guided through sessions designed to gradually extend sustained attention using adaptive feedback. A defining feature of the system is its multi-modal closedloop feedback architecture, which provides users with continuous, immediate feedback based on their internal neural activity. When the system detects motor imagery, it can generate adaptive visual feedback—such as movement animations or progress indicators—that help users refine their internal neural patterns. In cases where movement intention is observed, the system may issue subtle haptic cues, reinforcing the user's attempt and strengthening the brain–body connection. When the system identifies changes in cognitive workload, such as overload or reduced engagement, it automatically modifies the difficulty level, pacing, or complexity of the task to maintain optimal performance without causing mental fatigue. Together, these components—reinforcement learning, hybrid deep neural decoders, neuroplasticity prediction models, and multi-modal closed-loop feedback—form a sophisticated next-generation neuroadaptive platform. It provides a highly personalized, continuously evolving stimulation and training environment that adapts to each user's unique neural characteristics. This integration positions the system not only as a powerful tool for rehabilitation, cognitive enhancement, and human–machine interaction, but also as an advanced research framework for exploring the mechanisms underlying brain adaptation and learning.

2.5. Embedded Systems and Wireless IoT Integration

The system incorporates a microcontroller-based real-time neural acquisition module designed to capture neural signals with high temporal precision and extremely low latency. This embedded hardware unit is optimized for continuous monitoring of electrical activity from multiple neural sites, ensuring that even subtle fluctuations in cortical or peripheral neural patterns are detected reliably. By integrating low-noise amplifiers, high-resolution ADCs, and optimized firmware, the microcontroller is capable of processing raw neural data on the edge before transmitting it to higher-level systems. This on-device preprocessing significantly reduces computational overhead and minimizes data bottlenecks, enabling fast, uninterrupted operation essential for closed-loop neural interfaces and rehabilitation applications. To support distributed sensing and flexible deployment, the platform uses wireless communication for multi-site signal transmission. Multiple acquisition nodes can be placed across different body or brain regions, each communicating wirelessly via a secure, low-latency protocol. This architecture eliminates the constraints imposed by wired systems, allowing patients to move naturally during training or therapeutic sessions. The wireless layer synchronizes data from all acquisition points, compensating for transmission delays and ensuring that multi-site signals remain temporally aligned. This synchronized wireless network is crucial for decoding complex neural activities such as whole-limb coordination, bimanual motor planning, or distributed cognitive processes. Beyond local hardware capabilities, the system is tightly integrated with cloud-based AI infrastructures that continuously update and refine the neural decoding models. As data from different users accumulates, cloud servers perform large-scale training on powerful computational clusters, incorporating new patterns, adaptation curves, and user-specific behaviors. Updated models are securely pushed back to client devices, ensuring that each microcontroller and local processing unit benefits from the latest advancements in decoding accuracy and stimulation optimization. This cloud-driven update mechanism allows the system to improve over time, adapting to diverse populations while maintaining personalized performance for individual users. To make the technology practical for real-world healthcare environments, the system provides a mobile interface designed specifically for therapists, clinicians, and rehabilitation specialists. Through a streamlined mobile application, professionals can monitor neural activity in real time, adjust training protocols, and track long-term progress across multiple sessions. The interface presents complex neural metrics in intuitive visual formats—such as trend graphs, performance indices, and adaptive difficulty curves—allowing clinicians to make informed decisions without requiring advanced technical expertise. Additionally, the mobile platform supports remote monitoring and tele-rehabilitation, enabling continuous patient support regardless of physical location. Together, these components create a scalable and clinicianfriendly neurotechnology ecosystem: real-time neural acquisition at the edge, wireless multi-site communication for natural movement, cloud-based AI evolution for continuously improving accuracy, and a mobile interface that translates technical complexity into clinically actionable insights. This tightly integrated infrastructure enhances usability, supports personalized therapy, and opens the door to widespread adoption in both clinical and home-based rehabilitation settings.

3. RESULTS (HYPOTHETICAL/MODEL-BASED)

This study underscores the fundamental technological gap that exists between cutting-edge, research-grade soft bioelectronic systems and widely available commercial brain–computer interface (BCI) platforms such as i-BrainTech. Soft bioelectronic neural implants—engineered from ultrathin, stretchable, and tissue-conformal materials—offer an unprecedented level of spatial resolution, enabling them to record fine-grained electrophysiological signals at multiple cortical sites simultaneously. Their ability to capture micro-scale neural features, high-frequency activity, and distributed network dynamics makes them uniquely powerful for decoding motor intention, tracking neuroplasticity, and supporting advanced closed-loop control paradigms. However, these advantages come with a significant trade-off: such implants are inherently invasive, requiring surgical placement, long-term biocompatibility considerations, and highly specialized clinical infrastructure. These factors limit their accessibility and practicality outside of controlled research or medical environments. In contrast, commercial systems like i-BrainTech provide a highly accessible and noninvasive alternative, designed to be easily adopted by athletes, patients, and rehabilitation providers without the need for surgical procedures or advanced technical support. These platforms rely primarily on surface EEG, which, while safe and convenient, offers relatively low spatial resolution and limited sensitivity to deep or localized neural activity. As a result, their decoding precision, bandwidth, and ability to capture subtle neural dynamics remain constrained. i-BrainTech excels in usability and broad deployment but does not achieve the granular neural fidelity required for next-generation precision neurorehabilitation or fine motor intention decoding. To bridge this gap, our study introduces a hybrid neurotechnology model that combines the strengths of both approaches while mitigating their respective limitations. First, the integration of soft neural implants enhances signal precision by capturing high-resolution cortical activity unavailable through surface electrodes. This provides the system with a reliable source of detailed neural information necessary for accurate decoding and network-level monitoring. Second, usability is maintained through the incorporation of a wearable EEG interface, ensuring that the system remains practical, comfortable, and deployable in everyday clinical or training environments. Users and clinicians can interact with the system without the barriers typically associated with implant-only technologies. Additionally, the hybrid model incorporates AI-driven personalized neurofeedback, enabling real-time adaptation based on each user's evolving neural patterns, performance fluctuations, and rehabilitation needs. Reinforcement learning and deep neural decoders continuously refine stimulation, task difficulty, and feedback modalities, ensuring meaningful engagement and effective neuroplasticity induction. This adaptability transforms the system from a passive monitoring tool into an intelligent, responsive rehabilitation partner. Taken together, these components enable a true closed-loop rehabilitation ecosystem, where neural activity is recorded with precision, interpreted with high accuracy, and translated into personalized feedback that drives continuous improvement. This model supports dynamic interaction between brain and system, promoting deeper engagement, stronger neural reinforcement, and more robust functional recovery. Ultimately, the proposed integrated approach represents the next evolutionary stage of BCI-assisted rehabilitation, uniting the scientific advantages of invasive soft bioelectronics with the practicality and scalability of consumer-oriented noninvasive systems. By merging high-fidelity sensing, user-friendly interfaces, and adaptive AI, this hybrid BCI architecture sets a new benchmark for future neurorehabilitation technologies.

3.1. Discussion

This study draws attention to the significant technological distinctions between cutting-edge, research-level soft bioelectronic systems and widely deployed commercial brain–computer interface (BCI) platforms such as i-BrainTech. Soft bioelectronics, particularly implantable neural interfaces constructed from ultrathin and flexible materials, enable exceptionally high-fidelity neural recording. Their conformal contact with cortical tissue allows them to capture subtle electrophysiological signals with unparalleled spatial resolution and broad multi-site coverage. This capability offers researchers a detailed window into localized neural population dynamics, high-frequency activity, and distributed cortical network interactions. However, the same characteristics that make soft neural implants scientifically powerful also impose practical limitations: they are fundamentally invasive, require surgical implantation, and therefore are typically confined to controlled research or clinical environments with specialized expertise. In contrast, commercial BCI systems such as i-BrainTech prioritize accessibility, usability, and noninvasive operation. They are designed for widespread adoption among athletes, patients, and rehabilitation practitioners, enabling neurotraining without the need for surgical procedures or complex medical infrastructure. By relying on surface EEG, these platforms offer a simple, safe, and low-barrier entry point into neurofeedback-based training. Yet the trade-off is apparent: EEG alone cannot capture the fine-grained, deep cortical signals that invasive soft bioelectronics provide. As a result, commercial BCIs lack the neural precision necessary for applications requiring micro-scale decoding of motor intention, localized neuroplasticity monitoring, or high-bandwidth, closed-loop control. To overcome these limitations on both sides, our work introduces a hybrid neurotechnology model that strategically integrates the strengths of each approach. By incorporating soft neural implants, the system gains access to high-resolution neural information that dramatically improves decoding accuracy. At the same time, wearable EEG ensures that the overall system remains practical and user-friendly, allowing clinicians and therapists to operate the technology without specialized surgical requirements. This combination effectively balances scientific capability with everyday deployability. Beyond merging sensing technologies, the hybrid system also incorporates AI-driven personalized neurofeedback, enabling it to adapt continuously to each user's evolving neural patterns. Machine learning models—particularly reinforcement learning and deep neural decoding architectures—dynamically adjust stimulation intensity, task difficulty, and feedback modalities to optimize engagement and accelerate rehabilitation progress. This adaptability transforms the system from a static tool into an intelligent, interactive platform capable of tuning itself to the individual needs of each patient. Together, these components enable a genuine closed-loop rehabilitation framework: one in which high-fidelity neural data is recorded, interpreted in real time, and immediately translated into personalized corrective or supportive feedback. Such a tightly coupled loop promotes faster learning, deeper neuroplastic changes, and more effective therapeutic outcomes. In summary, this integrated hybrid approach represents the next major step forward in BCI-assisted rehabilitation. By uniting the precision of soft bioelectronics, the practicality of wearable EEG, and the adaptability of AI-driven neurofeedback, the system establishes a new paradigm for future neurorehabilitation technologies—one that is both scientifically advanced and clinically scalable.

4. CONCLUSION AND RECOMMENDATIONS

Soft bioelectronic networks and commercial EEG platforms represent two fundamentally complementary yet historically separate approaches within the brain–computer interface (BCI) domain. Soft bioelectronic systems, with their ultrathin, flexible, and tissue-conformal construction, provide an unprecedented level of signal fidelity by enabling direct access to cortical activity with high spatial resolution and multi-site coverage. In contrast, commercial EEG platforms offer unmatched ease of use, portability, and accessibility, making them suitable for broad deployment in sports training, clinical therapy, home-based neurotraining, and cognitive assessment. When evaluated individually, each modality contributes unique strengths but also exhibits inherent limitations—soft implants offer precision at the cost of invasiveness, while surface EEG offers accessibility at the expense of resolution. By strategically merging these two sensing paradigms into a unified hybrid architecture and augmenting them with AIdriven closed-loop mechanisms, it becomes possible to dramatically elevate the effectiveness of both motor and cognitive rehabilitation. The fusion of high-fidelity invasive data with broader noninvasive brain-state monitoring allows for more reliable neural decoding, richer representation of user intent, and more responsive neurofeedback loops. This hybrid strategy enhances the system's ability to adapt in real time, delivering personalized feedback that accelerates neuroplastic changes and improves long-term functional recovery. Looking ahead, several key areas require further investigation to fully realize the potential of such hybrid BCI systems. First, rigorous clinical validation is essential to determine the therapeutic impact, reliability, and user acceptance of hybrid sensing models in real-world rehabilitation settings. Second, the long-term safety, stability, and biocompatibility of soft bioelectronic implants must be carefully assessed through chronic implantation studies. Understanding tissue responses, durability, and signal stability over extended periods will be crucial for eventual translation. Third, adaptive AI models capable of aligning with each individual's neuroplasticity trajectory must be developed. These models should be able to personalize feedback strategies, stimulation protocols, and task progression based on evolving neural signatures. Finally, future research must consider how to design scalable, wearable-implant hybrid architectures that can support multi-region monitoring while remaining comfortable, compact, and suitable for everyday clinical use. Altogether, this research establishes a foundational framework for the development of next-generation closed-loop BCI rehabilitation systems. By combining the invasive precision of soft bioelectronics with the noninvasive accessibility of wearable EEG—and empowering both through intelligent adaptive AI—the field moves closer to creating rehabilitation technologies that are highly accurate, deeply personalized, clinically scalable, and capable of delivering transformative therapeutic outcomes.

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